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The Impact of Wildfire Pollution on Childbirth: Evidence from the 2006 Forest Fire in Indonesia

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Abstract

Climate-related events, such as drought and deforestation, substantially increase the frequency and severity of wildfires and, consequently, the amount of air pollutants in Indonesia. We combine childbirth data from the Indonesian Family Life Survey and aerosol data from NASA's Moderate Resolution Imaging Spectroradiometer to identify the effect of Indonesia's 2006 wildfire on newborns. More specifically, using a matching algorithm and a natural experiment approach, we show that the intensity of the fire decreased the weight of the newborns but did not affect either the sex or the gestation. Moreover, we also observe that weight loss is caused by exposure to pollutants during the early stages of pregnancy, not during the late stages.

Keywords: Natural Experiment; Wildfire; Air pollutants; Birth weight; IFLS; NASA-MODIS

1 Introduction

Climate change increases the severity and frequency of wildfires (Schwela, 2001). In addition, rapid demographic changes not only create planned deforestation, but also compound the effects of wildfires (Goldammer, 1999). These fires have devastating effects on wildlife, human health, the economy, and the climate itself (Harrison et al., 2009), creating a vicious cycle. Because of the effects of forest fires on the human population, there is an increasing need to understand the extent of their effects on human health (Bowman and Johnston, 2005). However, existing research on the human health impacts of forest fire pollution remains unclear (Fowler, 2003).

The adverse health effects of short-term increases in the levels of *fine particulate matter* ($PM_{2.5}$) in the air have primarily been studied in urban areas in relation to industrial or transportation sources (Brunekreef and Holgate, 2002; Katsouyanni et al., 2001, 1996; Pope III et al., 2004; Pope Iii et al., 2002; Samet et al., 2000). The health effects of increases in air pollution associated with burning forests have not received enough attention. A few studies were conducted in Southeast Asia, where large forest fires spread across Indonesia, which found some impacts of polluted air on exposed residents, such as increasing rates of hospitalization, respiratory problems, and even death (Brauer and Hisham-Hashim, 1998; Chew et al., 1995; Emmanuel, 2000; Kunii et al., 2002; Leech et al., 1998; Sastry, 2002).

Forest fires are random events that have a predictable seasonal trend as well as an idiosyncratic component. Indonesia is known to be one of the countries most affected by these fires; moreover, their frequency and severity vary from year to year. Uncontrolled fires across Indonesia burn large areas of peatland and create vast palls of smoke on an almost annual basis. The occurrence and intensity of wildfire smoke are highly associated with the El Niño-Southern Oscillation (ENSO) cycle.[1]

[1]Since 1950, extremely strong ENSO events have occurred during three periods: 1982/83, 1997/98 and 2015/16. Historical records of the 1997/98 and 2015/16 seasons were strongly correlated with extreme forest fires. However, there is little recorded evidence about forest fires in the 1982/83 season, although some claim the fire intensity was very high

The most severe ENSO event was the one in 1997/98. It affected six provinces in Indonesia, covering 10 million hectares of land across the country. It was estimated that this event released between 2.97 and 9.42 billion tons of carbon dioxide into the air, and there was an economic loss of approximately 4.5 billion USD (Heil, 2007; Field et al., 2016; Koplitz et al., 2016).

The World Health Organization released a report for Indonesian 1997/98 forest fires, which stated that air pollution was responsible for 20 million people's respiratory problems (Dennis, 1999; Aditama, 2000). According to Dennis (1999), approximately 75 million Indonesians were affected to some extent, almost 300,000 people were hospitalized, more than half a million people received some degree of medical treatment treatments, and there are almost a million additional people who practiced self-treatment.

In general, the frequency of visits to clinics and hospitals doubled during the fire and haze seasons, and this increase in patients drastically declined with the end of the wildfire (Aditama, 2000). Moreover, most of those cases were related to respiratory problems. Additionally, approximately 20% of the deaths in affected regions were because of fires (Jones, 2006).

In this study, we analyze the effects of the 2006/07 ENSO season for two reasons: (*i*) by pure chance, the Research and Development (RAND) Corporation conducted a precise large-scale survey in 2007, which perfectly overlaps with the effects that the ENSO could have on childbirth; and (*ii*) although its intensity and impact is not as large as the 1997/98 and 2015/16 ENSO seasons, it is still the third largest event with measured pollution data.[2] Indeed, the 2006/07 ENSO season affected nearly 3 million hectares and dramatically increased wildfires and air pollution. This event was estimated to have released up to 2 billion tons of carbon dioxide into the atmosphere, making Indonesia the third

during this period too (Dennis, 1999).

[2]See figure 4.

largest greenhouse gas polluter in 2006 (Ballhorn et al., 2009; Marlier et al., 2015).

There is evidence showing the relation between forest fires and human health. For example, wildfires have a detrimental long-term impact on children's lung development (Black et al., 2017). Even in rich countries, excessive fires lead to premature deaths (Kollanus et al., 2017). Moreover, forest fires can lower IQ scores and school performance in children (Banerjee, 2016); increase the difficulty of performing physical activities due to negative health-related outcomes (Frankenberg et al., 2005); and are associated with lower height (Rosales-Rueda and Triyana, 2019). However, no study has investigated the impact of forest fires on newborns' health.[3]

We pay particular attention to two empirical studies that investigated the impact of the 1997 forest fire in Indonesia. Frankenberg et al. (2005) used 1993 and 1997 family survey data and relatively coarser satellite measurements of the aerosol index to differentiate between exposed and unexposed locations. Because of the large effect of 1997, the authors found a significant effect even with coarse satellite measurements.[4] Namely, the authors find a significant positive effect on 'difficulty of carrying a heavy load'. However, they failed to find an impact on two other outcomes: respiratory problems and general health status.

Rosales-Rueda and Triyana (2019) constructed a panel to study the impact of air pollutants in 1997 on children's health. They found that three years after exposure, infants who were 13-24 months old in 1997 were shorter than other infants. Similarly, 10 years after exposure, children who were in utero during 1997 were also shorter, and this result persisted even 17 years later. They also found weaker results regarding lung capacity deterioration. Nevertheless, their study did not use an experimental approach.

[3]In addition, our results are derived from a natural experimental approach, while many of the mentioned studies (with a few exceptions) were mostly examining correlations.

[4]This study would not have worked with smaller fires such as that of 2006, as shown in figure 1 and table 7.

In our study, we focus on childbirth weight. Although scholars have studied the relationship between air pollution and birth weight, the mechanism that links those two variables is still unclear. Some of the findings revealed a strong correlation with early pregnancy exposure, while others found that exposure during late stages of pregnancy was associated with a lower birth weight. For example, an association between low birth weight and exposure to pollutants during early stages of pregnancy included studies on the effects of carbon monoxide, nitrogen dioxide, and sulfur dioxide in South Korea (Ha et al., 2001); PM_{10} and carbon monoxide in Brazil (Gouveia et al., 2004); and total suspended particles, sulfur dioxide, and nitrous oxides in the Czech Republic (Bobak, 2000). On the other hand, other studies found an association between low birth weight and exposure to pollutants during late stages of pregnancy, including studies on carbon monoxide and nitrogen dioxide concentrations in Australia (Mannes et al., 2005) and air pollutants such as PM_{10} and $PM_{2.5}$ (Bell et al., 2007) and carbon monoxide and nitrogen dioxide (Morello-Frosch et al., 2010), both in California. Moreover, to the best of our knowledge, none of the previous studies on this topic used an experimental approach. On the other hand, our case has the great advantage that the intense 2006/07 fire makes it a natural experiment.

We combine the relatively new high-resolution satellite data of aerosol optical depth (AOD) coded by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and the large-scale Indonesian Family Life Survey (IFLS) from 1999/2000 and 2006/2007.[5] Because the ENSO event is exogenous, our data become a natural experiment and allow us to identify the effect of the 2006/07 forest fire on newborns' weight in Indonesia. Using a matching algorithm, we show that fire air pollution decreased birth weight. Moreover, this effect is significantly higher in areas heavily affected by pollution, and is

[5]The comparison with the IFLS from 2013/2014 is weaker in the sense that the fire in that year was much stronger than that in 1999/2000, thus making it difficult to detect a statistically significant effect. See figure 4 and table 8.

caused during early stages of pregnancy, not during the late stages.

2 Background

In 1995, the Indonesian government had the initiative to open 1.5 million hectares of peatlands to achieve self-sufficiency of rice (called the Mega Rice Project). To do so, they built drainage canals on those peatlands. These canals are one of the factors that triggered the massive 1997/98 forest fires (Harrison et al., 2009). It was also estimated that 80% of the smoke that resulted from those fires came from peatlands that burned and spread to the islands of Sumatra and Kalimantan. Additionally, although the magnitude of the fire was definitely unplanned, most of the fires started intentionally, mainly for timber plantations and palm oil concessions (Aiken, 2004). Indeed, land concession steadily increased from 106,000 hectares in 1967 to 2.5 million hectares in 1997. Since 1997, the most intense forest fires in Indonesia occurred in 2015, with 33% of the affected area coming from peatlands (approximately 2.6 million hectares). Moreover, both events resulted in severe transboundary haze surrounding Southeast Asia.[6]

Indeed, every year, Indonesia suffers from fires, which mainly originates from human activity. However, drought and some other random events can escalate these fires and greatly increase their effect, which is what happened in the two cases mentioned above. Moreover, excluding the 1997 and 2015 fires, the most noticeable was the one in 2006, which is the event of our study. Similar to the previous two cases, it is estimated that the fire was greatly influenced by the burning of peatland areas, where more than 50% of emissions came from timber and palm oil concessions (Marlier et al., 2015; Ballhorn et al., 2009).

[6]However, neighboring countries (especially Singapore) are affected by Indonesia's fires on a yearly basis.

Most of the attention has been focused on the 1997 fire because of its severity. We analyze the 2006 fire because there are more precise pollution data, and the IFLS allows us to look at this issue from an experimental perspective.

3 Data and Methodology

To measure the effect of air pollution on childbirth, we combine two datasets: NASA-MODIS AOD data and IFLS data on pregnancy and childbirth outcomes. Then, we regard the 2000 IFLS data as the control group and the 2007 data as the treatment group. The characteristics of each dataset are described below.

3.1 NASA-MODIS Aerosol Optical Depth

Since 2000, NASA has used MODIS technology to measure aerosol concentrations in the atmosphere. MODIS's data grid size has a precision of 0.1° latitude and 0.1° longitude.[7] This is a drastic improvement compared to the precision used in previous studies (Frankenberg et al., 2005; Rosales-Rueda and Triyana, 2019), which used MODIS's predecessor, NASA's Total Ozone Mapping Spectrometer (TOMS), for the aerosol index, with a grid of 1° latitude and 1.25° longitude.[8] Therefore, MODIS data are approximately 125 times finer than TOMS data. To measure aerosol exposure, we average the AOD covering a region.[9]

Indonesian district sizes range from 16.47 km^2 to more than 2,000 km^2, with an average of 283.08 km^2. Thus, in the old measurement system (TOMS), one grid can cover the seven largest districts.

[7] 11.0574 km × 11.132 km on average

[8] 110.574 km × 139.15 km on average

[9] More specifically, we use the right Riemann sum that covers a particular area.

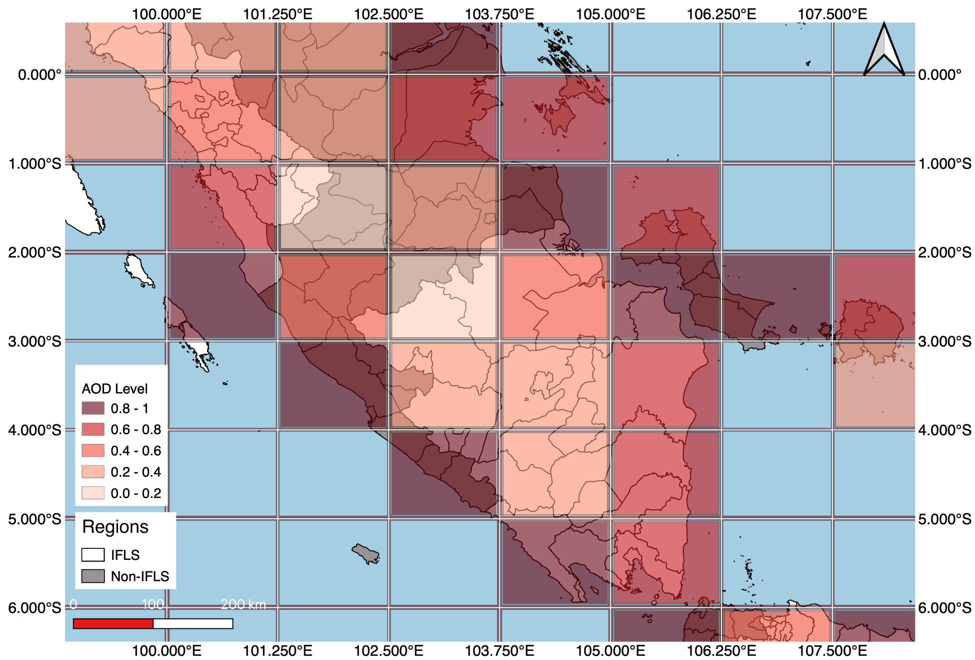
However, air pollution can drastically change even between neighboring districts. On the other hand, MODIS's AOD measurements are finer than the average size of districts. Thus, with these richer data, we can obtain more precise and more varied observations of the AOD among districts. The difference in grid size between the TOMS (figure 1(a)) and MODIS (figure 1(b)) data is shown in figure 1.[10]

The whole Indonesian territory is covered by 78,625 MODIS grids, while the thirteen provinces in the IFLS dataset are covered by 30,062 MODIS grids. The AOD index ranges from 0 (clear sky) to 1 (heavy haze and pollution). To define what is considered an 'intense' or 'normal' fire, we use monthly AOD data over almost a decade, from March 2000 to December 2010. With these monthly data, we can see that forest fires in Indonesia are seasonal; during the forest fire months (FFMs), from August to November, the AOD index often reaches the most hazardous level of 1, whereas during the non-forest fire months (NFFMs), from December to July, the AOD index is never higher than 0.78 in our sample and often below it. See figure 2 below.

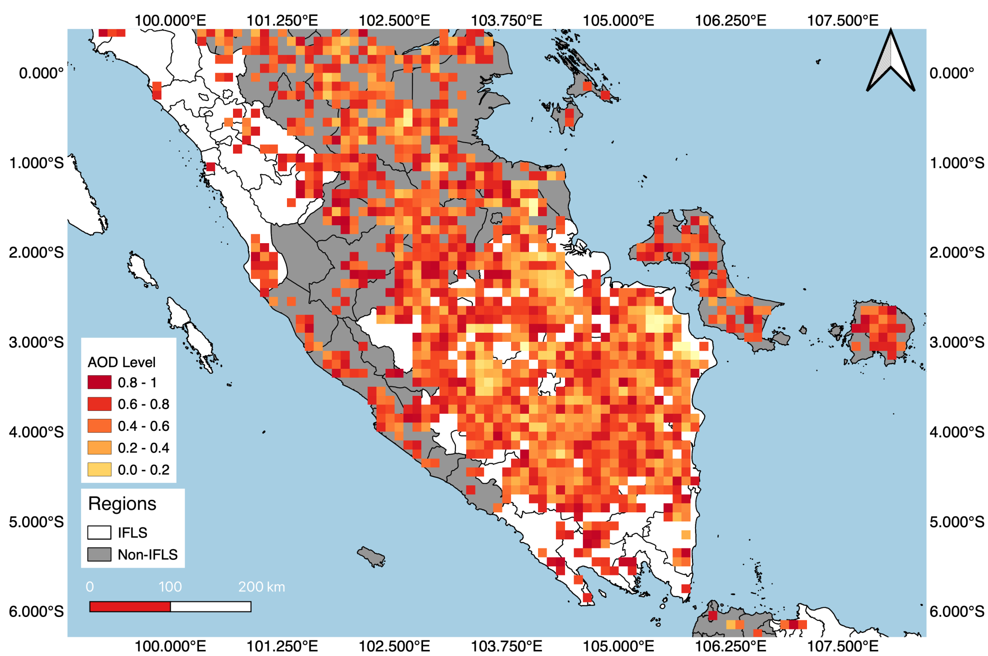
Thus, based on the observed data, we define a district as having an intense fire (IF) if the AOD exceeds the threshold of 0.78 in at least one of the four FFMs, and we define the dummy variable IF to indicate this event. Indeed, figure 3 shows how the distribution of AOD during NFFMs is basically identical when comparing 2006 and the rest of the 2000-2010 period, while during FFMs, there is a clear difference in the distribution of AOD measures when comparing 2006 with the rest of the 2000-2010 period.

[10]We replicated the analysis of columns (3) and (4) of table 2 but used TOMS-sized grids (coarser). Obviously, the results of column (3) still remain because in that case, the coarser data are used only as a matching variable. On the other hand, the results of column (4) are lost due to the noise introduced by less precise AOD measures. The results are shown in appendix table 7.

Figure 1: Comparison of grid sizes



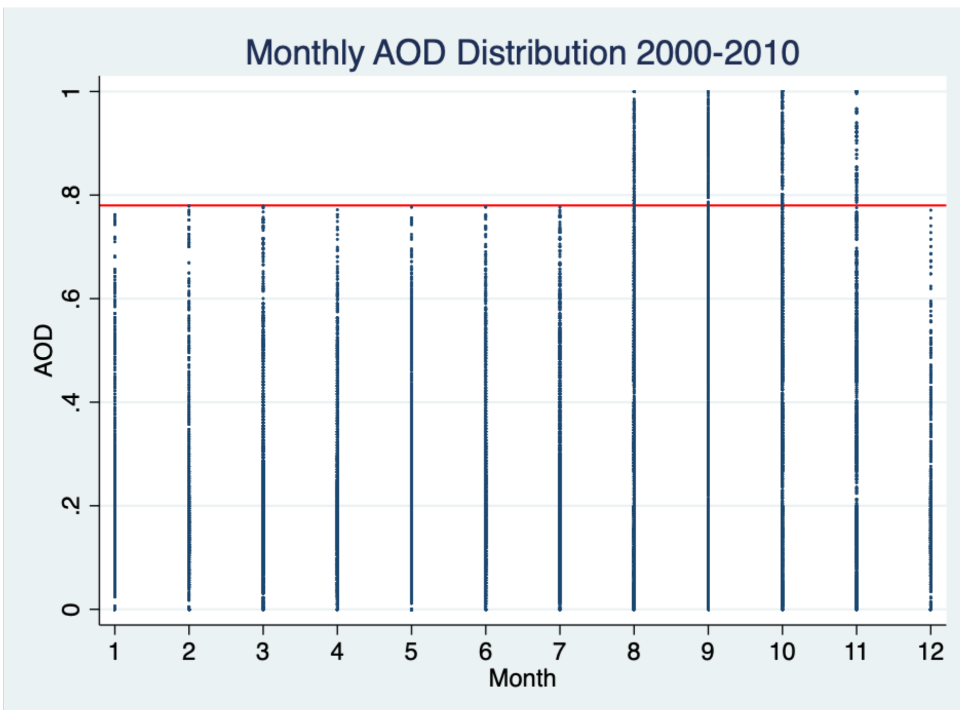
(a) Coarse MODIS data (same grid size as TOMS)



(b) Fine MODIS data

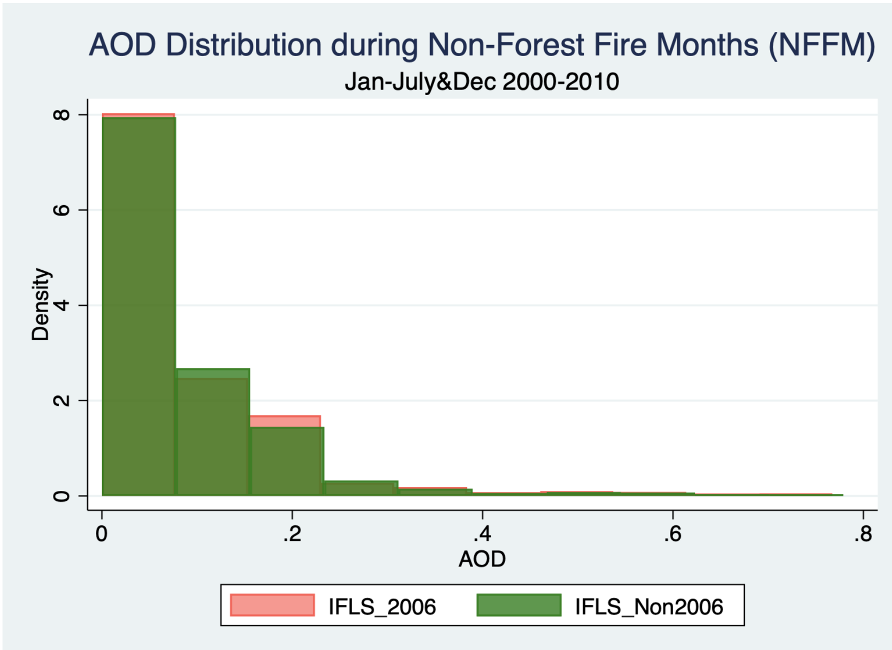
Grid comparison between the TOMS and MODIS data, overlapping the provinces and districts covered by IFLS in the southern half of Sumatra.

Figure 2: Monthly AOD distribution over Indonesian regions from March 2000 to December 2010

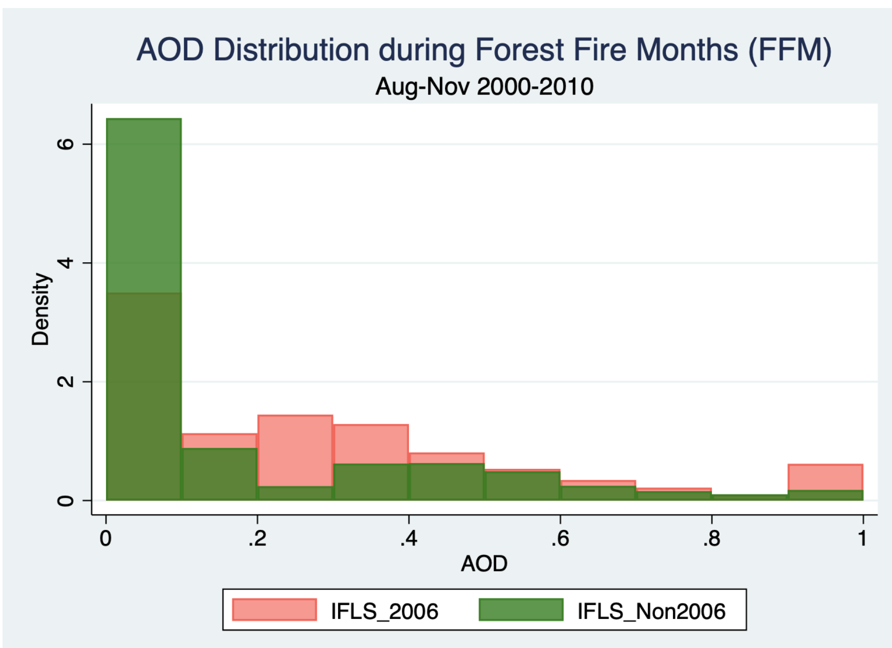


Monthly scattered AOD over the 2000-2010 period. Months are represented by numbers from January = 1 to December = 12. The NFFMs never exceed the 0.78 threshold.

Figure 3: AOD comparison between the FFMs and NFFMs



(a) December to July



(b) August to November

AOD comparison during the FFMs and NFFMs in the IFLS regions. The $IFLS\_2006$ series refers to the 2006 AOD observations within districts covered by the IFLS. $IFLS\_Non2006$ refers to observations between 2000 and 2010, excluding 2006, that are covered by the IFLS.

3.2 IFLS Data

The IFLS is conducted in 13 provinces: North Sumatra, West Sumatra, South Sumatra, Lampung, Jakarta, Jogjakarta, West Java, Central Java, East Java, Bali, West Nusa Tenggara, South Kalimantan, and South Sulawesi. Each of these provinces is divided into several districts (235 districts or an average of more than 18 districts per province).

We use two samples: the survey conducted in 2000 and the survey conducted in 2007. Because the fire in 2006 was unquestionably severe, we regard the first survey as the control and the second survey as the treatment. Our main outcome of interest is the weight of the newborns. Moreover, we omit the survey observations based on whether the newborns had a chance to have been affected by either the FFMs of 1999 or those of 2006. That is, we analyze data from babies born during the FFMs or at most nine months after the last FFM (November) of the relevant year. More precisely, for the 2000 (2007) survey, we consider only households whose babies were born between August 1999 (2006) and August 2000 (2007). With this restriction, our sample decreased from 1,641 to 1,375 observations. Table 1 shows the sample sizes and the average weight in kilograms across time and the IF dummy variable.

Table 1: Average birth weight in kilograms

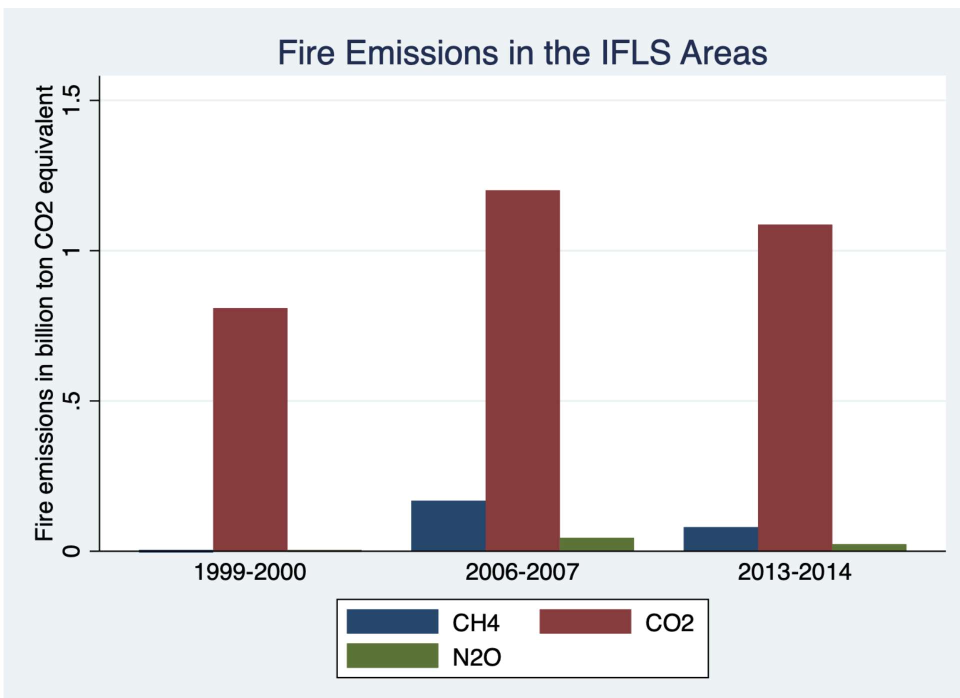
	2000 IFLS	2007 IFLS
Total number of newborns	702	939
	Aug 1999/Aug 2000	Aug 2006/Aug 2007
Newborns possibly affected by the FFM	654	721
Average weight (all districts)	3.177 Kg	3.119 Kg
Average weight in low-AOD districts	3.145 Kg	3.116 Kg
Average weight in high-AOD districts	3.392 Kg	3.134 Kg

Note that the weight decreased in both cases: districts with low and high AODs during the FFMs.

Moreover, in the 2000 IFLS sample, childbirth weight was higher in high-AOD regions. This finding could be related to the higher development in high-AOD regions in that year, which later slowly flips becoming higher in low-AOD regions by 2013. We further discuss this phenomenon in section 5.

Thus, our treatment variable $Treat_1$ will equal one for observations from the second survey that could have been affected by the FFMs of that year ($Treat_1 = 1$ for 721 cases) and will equal zero for observations from the first survey that could have been affected by the FFMs of that year ($Treat_1 = 0$ for 645 cases).

Figure 4: Total fire emissions from the areas and years covered by the IFLS



The 2000 IFLS pregnant women were affected by fire pollution from 1999 to 2000. The 2007 IFLS pregnant women were affected by fire pollution from 2006 and 2007. The 2014 IFLS pregnant women were affected by fire pollution from 2013 and 2014. CH_4 = methane; CO_2 = carbon dioxide; N_2O = nitrous oxide. This figure was coded using data from The Copernicus Atmosphere Monitoring Service.

The IFLS was also conducted more recently, in 2014. However, as shown in figure 4, the fires in those years were also relatively severe, making the comparison with the 2007 survey difficult. Thus, it would not make sense to use the 2013/2014 newborns as a control.[11]

In addition, we also checked whether fire has larger effects during the early or late stages of pregnancy. That is, we define two more treatment variables: (*i*) $Treat_2$ will be analogous to $Treat_1$, but restricting attention to those newborns that were conceived during one of the four FFMs ($Treat_2 = 1$ for 235 cases and $Treat_2 = 0$ for 199 cases).[12] (*ii*) $Treat_3$ is also analogous to $Treat_1$, but restricting attention to those newborns that were born during the FFM of either 1999 or 2006.[13]

Other variables we use are the sex of the newborn ($sex = 1$ for male); the length of pregnancy ($gestation$ in months); the mother's age (age in years); whether the mother is married ($marital = 1$ for married); whether she lives in an urban area ($urban = 1$ for an urban area); whether she took iron pills as supplements ($iron = 1$ if she took the pills); and her education level, which was coded as one of three categories (edu_1, edu_2, edu_3).[14]

3.3 Methodology

We want to identify the effect that the 2006 fire had on newborns. From Table 1, we could simply compare averages and obtain a difference-in-differences (DiD) estimation. However, the outcome we are interested in is childbirth, which is an event that happens only once. Even if a household is in both surveys, the chances that the same mother happens to be pregnant in 2000 and 2007 is very

[11] Appendix table 8 shows that although the point estimate is negative, the coefficients are not significant.

[12] The month of conception was calculated based on the self-reported gestation and the delivery date. Some of the self-reported observations are clearly incorrect, as there are observations of less than 2 months as well as more than 20 months. Upon contacting RAND, we suspect there was confusion between weeks and months, both of which are measured. Thus, in cases where the length (in months) was too short, we multiplied the number by 4.3, which is the average number of weeks in a month. For the cases in which the length was too long, we divided it by 4.3. The number of observations that underwent this adjustment is 23. Our results are robust to omitting these observations.

[13] That is, it does not make sense to include babies born in August 2000 and August 2007.

[14] The three categories are up to high school (edu_1), college (edu_2), and 'informal education' (edu_3).

small, which would greatly reduce our sample size.[15] Instead of a DiD estimator, we use a matching algorithm, which is a powerful tool to identify the effect of natural experimental events (Heckman et al., 1998). More specifically, we use the multivariate distance matching method.[16]

In our context, the matching algorithm uses a vector of covariates x in a Euclidean space X to pair households in the 'control' group (2000) with households in the 'treatment' group (2007), based on the 'distance' between those households in the X space. To evaluate the effect of the 2006 fire, we will estimate both the average treatment effect (ATE) and the average treatment effect on the treated (ATT).

The interpretation of each metric is slightly different. The ATE measures the difference in the outcome variable between newborns in the second and first surveys. In contrast, the ATT mimics a counterfactual analysis to estimate the effect that the 2006 fire had on newborns in the second survey. Because those two estimators provide valuable information, we include both in our results.

4 Results

As outcome variables, we focus on birth weight. At the end of this section, we will also discuss sex and gestation. In the IFLS data, an observation is a birth; thus, it contains characteristics of both the mothers and newborns. We match pairs of mothers in each of the surveys according to a vector of main relevant mother characteristics x^m, which contains information on the previously defined variables age, $marital$, $urban$, $iron$, edu_1, edu_2 and edu_3. In addition, we also perform a robustness analysis adding one of the following covariates to the matching algorithm: (i) pregnancy length ($gestation$) and the

[15]Ignoring these problems, the DiD estimator using the high-AOD region dummy variable as the treatment would be -0.22 grams, with a p-value of 0.028. This is comparable to, but underestimates, the results in column (4) of table 2.

[16]We use Mahalanobis distance matching. Alternatively, our results are robust to using the propensity matching score.

newborn's sex (*sex*), (*ii*) the average AOD of the mother's location during the FFM (*ave_AOD*), (*iii*) and the previously defined dummy variable IF that denotes intense fire. Table 2 shows the ATE and ATT under several matching vectors.

Table 2: Effect of the 2006 fire on birth weight

	(1)	(2)	(3)	(4)
		All Regions		High-AOD Regions
ATE	-0.0592*	-0.0625*	-0.0746**	-0.247*
	(0.0338)	(0.0347)	(0.0329)	(0.128)
ATT	-0.0656*	-0.0660*	-0.0758**	-0.287**
	(0.0356)	(0.0360)	(0.0336)	(0.117)
Observations	1,313	1,313	1,313	154
age, marital, urban, iron	✓	✓	✓	✓
gestation, sex	✓			
ave_AOD		✓		
Intense Fire			✓	

* $p < 0.05$, ** $p < 0.01$. Columns (1) to (3) use all the sample, but different matching covariates. Column (4) uses only the main covariates, but restricts attention to the subsample of intense fire regions ($IF = 1$). All columns use Mahalanobis distance matching.

Because pollution associated with intense fire has negative externalities, one expects that the 2006 wildfire would have a significant effect in the entire region, which is what we can see in columns (1) to (3) of table 2. The fire caused an average decrease in birth weight of approximately 5 to 7 grams. Moreover, if we look exclusively at the intense fire regions, the effect is drastically higher, as shown in column (4). A baby born in a region that exceeds the 0.78 AOD threshold was almost 30 grams lighter in 2006 (the ATT effect) because of wildfires.

The next question we answer is whether pollution affects early or late stages of pregnancy more intensively. To do so, we look at two subsamples. First, we pay attention to newborns who were estimated to have been conceived during the FFMs. Second, we pay attention to babies who were born during the FFMs. The results are shown in table 3.

Table 3: At what stage of pregnancy does pollution affect the newborns' weight?

	(1)	(2)	(3)	(4)
	Conception During the FFMs		Birth During the FFMs	
ATE	-0.105**	-0.275**	0.00441	-0.228
	(0.0514)	(0.123)	(0.0581)	(0.190)
ATT	-0.121**	-0.322**	0.0124	-0.173
	(0.0508)	(0.124)	(0.0599)	(0.190)
Observations	417	48	396	41

* $p < 0.05$, ** $p < 0.01$. Columns (1) and (3) use the entire sample, and the covariates used for matching are age, marital, urban, iron, and IF. Columns (2) and (4) restrict attention to the subsample of intense fire regions ($IF = 1$), and use age, marital, urban, and iron as covariates for matching. All the columns use Mahalanobis distance matching.

From columns (1) and (2) in table 3, it is evident that fire emissions affects newborns' weight during early pregnancy. Indeed, the average weight loss across all regions is above 10 grams, and the effect in intense fire regions on 2006 newborns is above 32 grams. On the other hand, babies born during the FFMs did not show a significant effect, and indeed, the point estimate is positive when looking at the whole sample.

Finally, table 4 shows that fire did not cause premature birth, nor did it have an effect on the sex of the newborn.

5 Discussion on Robustness

Jakarta. We investigate whether the effect of our results is driven by Jakarta. There are two reasons why the capital may be causing problems in our results. First, Jakarta is an outlier in terms of wealth and development. Income is much higher than that in the rest of Indonesia, there are increasingly

Table 4: Gestation and sex

	(1) Pregnancy Length (weeks)	(2)	(3) Sex (male=1)	(4)
ATE	-0.0938	-0.0495	-0.0305	-0.0142
	(0.127)	(0.298)	(0.0288)	(0.0967)
ATT	-0.108	-0.160	-0.0252	-0.0133
	(0.122)	(0.269)	(0.0301)	(0.106)
Observations	1,313	154	1,313	154

* $p < 0.05$, ** $p < 0.01$. Columns (1) and (3) use the entire sample, and the covariates used for matching are age, marital, urban, iron, and IF. Columns (2) and (4) restrict attention to the subsample of intense fire regions ($IF = 1$), and use age, marital, urban, and iron as covariates for matching. All the columns use Mahalanobis distance matching.

better hospitals, and large metropolitan areas have self-generated pollution. It is difficult to know whether the fire will compound the negative effects of pollution in Jakarta, or perhaps people who live in Jakarta developed some sort of resilience to pollution.

Second, as shown in appendix table 9, the AOD threshold of 0.78 is clearly distant (above or below) from the measure that defines intense fire regions among the rest of the provinces; however, the measure for Jakarta was almost 0.78. Because of these two reasons, we show that our results are robust to removing Jakarta from the sample (table 5). If anything, the point estimates represent a more drastic decrease in weight.

No Parallel Trend. We used a matching algorithm instead of the DiD method. In section 3.2, we discussed one reason why we are reluctant to use a DiD estimator. In addition, we believe that the *parallel trend* assumption is also not satisfied, thus making our claim stronger. We discuss this point by using the Human Development Index (HDI).

The HDI is one of the best indicators that summarizes economic progress and health. The institution known as Statistics Indonesia (Badan Pusat Statistik, BPS) measured the HDI by province in 1999,

Table 5: Effect of the 2006 fire on birth weight

	(1)	(2)	(3)
		All Regions	
ATE	-0.0622*	-0.0797**	-0.0783**
	(0.0369)	(0.0395)	(0.0356)
ATT	-0.0648*	-0.0824*	-0.0809**
	(0.0389)	(0.0432)	(0.0363)
Observations	1,168	1,168	1,168
age, marital, urban, iron	✓	✓	✓
gestation, sex	✓		
ave_AOD		✓	
Intense Fire			✓

The same as table 2, but excluding Jakarta from the sample. * $p < 0.05$, ** $p < 0.01$. All the columns use Mahalanobis distance matching.

2006, 2007, 2013 and 2014. Because 2000 is missing, we take the 1999 HDI as representative for the 3rd IFLS; the averaged 2006 and 2007 as representative for the 4th IFLS; and the averaged 2013 and 2014 HDI as representative for the 5th IFLS. Moreover, for the reasons explained above, we omit Jakarta from the HDI calculations.

Table 6: HDI by region

	1999	2006/2007	2013/2014
Low-AOD Regions	63.31	69.63	71.53
High-AOD Regions	64.30	70.65	70.86

The table coded using the BPS data at the province level.

Table 6 shows that the HDI was relatively higher in high-AOD regions in 1999. However, by the 2013/2014 period, the HDI increased faster in low-AOD regions. In addition, this also relates to two other points from our study. First, the high-HDI in high-AOD regions in 1999 can be related to the difference in childbirth weight of that year, as seen in table 1. Second, the flip in the HDI from 2006/2007 to 2013/2014 can be an additional reason why we should not use the fifth IFLS as a control group.

6 Conclusions

We combined the 2000 and 2007 IFLS data with aerosol indicators from NASA-MODIS to identify the impact that the 2006 Indonesian forest fire had on the health of newborns. Using kernel matching between newborns that could have been affected by the fire months of the fires in 1999 and 2006, we show that the 2006 fire decreased the average birth weight of Indonesian newborns by approximately 5 to 7 grams. Moreover, we also show that this decrease is caused by exposure to pollutants during early pregnancy, not during the late stages of pregnancy.

Scholars have studied the relation between air pollution and health. Nevertheless, there are very few studies on the effect of pollution caused by fire on newborns. Although the literature has divided opinions regarding at what stage air pollution affects the fetus more severely during pregnancy, we believe our experimental approach provides strong evidence in favor of those studies that claim that pollution impacts the development of the embryo early in the gestation period.

Although our approach has an advantage compared to previous studies, a natural experiment still has limitations. In addition, the IFLS is clustered by province instead of randomly sampling people from all over Indonesia. This phenomenon probably does not invalidate the direction of our results (lower birth weight), but it could affect the point estimates (i.e., the ATT measured in grams could be different). In addition, although it occurred in very rare cases, the IFLS data itself had obvious errors (i.e., gestation of more than 20 months); nevertheless, our results are robust to either imputing or omitting those errors. Finally, it was a large coincidence that the third largest forest fire occurred in 2006, affecting the majority of mothers interviewed in the 2007 IFLS. On the other hand, it was unfortunate that the 2013/2014 period had much pollution, making the 2014 IFLS unusable as a control group.

Beyond the obvious recommendation that forest fires should be prevented and deforestation should be avoided, our results have sharper policy implications. Namely, since the health of newborns is affected by exposure to pollutants at the beginning of pregnancy, governments that can predict seasonal fires can launch a campaign to discourage people from becoming pregnant during the fire season. Moreover, this campaign can be regional by targeting areas that are historically more likely to be affected by fire.

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A Additional Tables

Table 7: Coarser AOD grids introduce noise

	(1) All Regions	(2) Intense Fire Regions
ATE	-0.0681**	-0.115
	(0.0337)	(0.117)
ATT	-0.0589*	-0.104
	(0.0340)	(0.108)
Observations	1,313	214
age, marital, urban, iron	✓	✓
High-AOD dummy variable	✓	

* $p < 0.05$, ** $p < 0.01$. Intense Fire was defined using the coarser AOD grid. Column (1) mimics column (3) from table 2, and column (2) mimics column (4) from 2.

Table 8: Less severe fire comparison: 2007 versus 2014

	(1) All data	(2) Intense Fire Regions
ATE	-0.0376	-0.0394
	(0.0308)	(0.0852)
ATT	-0.00604	-0.0174
	(0.0297)	(0.0832)
Observations	1,430	211
age, marital, urban, iron	✓	✓
High-AOD dummy variable	✓	

The 2014 IFLS is used as the control group instead of the year 2000. Column (1) mimics column (3) from table 2, and column (2) mimics column (4) from 2.

Table 9: 2006 FFMs AOD by province

Province		Max AOD during the FFMs
	Low 2006 AOD	
Bali		0.584
Jakarta Raya		0.775
West Java		0.609
Central Java		0.554
East Java		0.588
West Nusa Tenggara		0.480
South Sulawesi		0.530
Yogyakarta		0.528
mean		
	High 2006 AOD	
South Kalimantan		0.998
Lampung		0.874
West Sumatra		0.962
South Sumatra		0.997
North Sumatra		0.982

Maximum AOD during the 2006 FFMs. Jakarta is the only province that is near the threshold of 0.78; all the other provinces have a very clear low or high AOD.